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Investigating Yield Variability and Technical Efficiency of Smallholders Pineapple Production in Johor

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Abstract: This research investigates the efficiency of pineapple production in Malaysia using the stochastic frontier model with flexible risk features and a sample of 290 pineapple farms by smallholders in Johor. The results of the study indicate that the trans log model is the best match for the mean output function, while input factors, such as sucker, fertilizer, agrochemicals, labor, and hormones, have a positive effect on pineapple yield with rising returns to scale. The study also finds that fertilizers and hormones are risk increasing inputs, whilst sucker is classified as a risk decreasing input. The total farm-specific characteristics account for the difference in the mean technical efficiency, which is estimated to be 68.1%. The study shows that, on average, 31.9 percent of the potential output is wasted owing to technical inefficiency and production risks in inputs. However, the optimal production of pineapple is facilitated by the application of the best agricultural techniques.

Keywords: pineapple; production risk; technical efficiency; stochastic frontier analysis

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Citation: Muhamad, M.Z.; Shamsudin, M.N.; Kamarulzaman, N.H.; Nawi, N.M.; Laham, J. Investigating Yield Variability and Technical Efficiency of Smallholders Pineapple Production in Johor. *Sustainability* **2022**, *14*, 15410. https://doi.org/10.3390/su142215410

Academic Editor: Hossein Azadi

Received: 23 September 2022
Accepted: 15 November 2022
Published: 19 November 2022

1. Introduction

Pineapple's role in Malaysia's economy extends beyond its role as a source of food, as its cultivation also provides farmers with a crucial source of revenue and new employment opportunities [1]. Pineapple is produced throughout all states in Malaysia. The amount of pineapple harvested fluctuated between the years 2000 and 2020, as shown in Figure 1. This entails the focus that is being provided by the government through the myriad of policies that are being mandated through the Malaysia Plans. The Eight Malaysian Plan (2001–2005), the Ninth Malaysian Plan (2006–2010), the Tenth Malaysian Plan (2011–2015), and the Eleventh Malaysian Plan (2016–2020) each focused on and highlighted different crops [2–5].

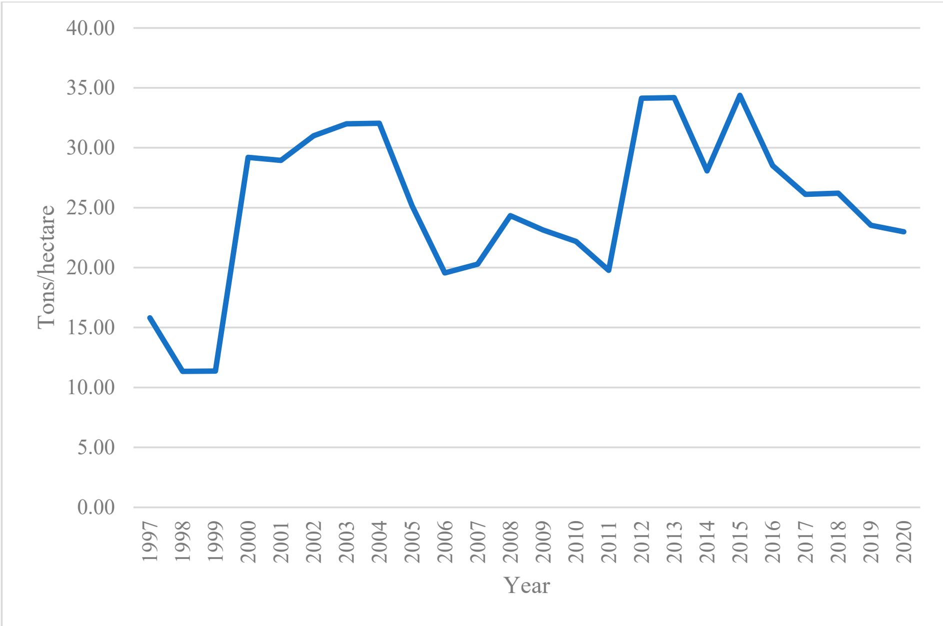

Figure 1. Yield of pineapple (1997–2020). Source: Malaysian Pineapple Industry Board, 2012, 2019a, and 2020b [6–12].

In accordance with the Ministry of Food and Agriculture Industry (MAFI), which was effectively established during the Eighth Malaysia Plan (8th-MP) (2001–2005) [2], pineapple cultivation has been selected as one of the eight locally grown fruits that are encouraged in the Third National Agricultural Policy Plan (DPN3) [13]. On the basis of its economic potential and value, the pineapple commodity has been nominated as a commodity that should be developed in order to become a flourishing industry that is more competitive, resilient, and viable in the domestic market during the next five years (2005–2010) in accordance with the strategic planning that was carried out by MAFI through the eighth-MP between the years of 2004 and 2010, which led to a rise in the total area of land that was owned by small-scale farmers. The purpose of this planning was to expand the size of the planting area where pineapples are grown as well as the infrastructure, attract more growers and entrepreneurs to the industry, and devise more effective strategies for cultivating and marketing various products of pineapple. The responsible agency in the governing pineapple industry, the Malaysian Pineapple Industry Board (MPIB), was working on a long-term strategy that would involve the exploration of new regions for farming, an increase in productivity, and a resolution to the pineapple shortage in the processing factories [14]. The Eleventh Malaysian Plan allocated a total of 22.07 million USD to be invested in the pineapple industry [5]. As a consequence of good prospects in the pineapple industry, the allocated funds for the Twelfth Malaysian Plan increased to a total of 29.06 million USD [15]. The MPIB has been encouraging farmers to cultivate pineapples with the assistance of these funds in order to increase the amount of revenue that can be generated by small-scale farmers.

Small-scale farmers, particularly those located in developing countries, frequently face production challenges, such as uncertainty and variation in their crops [16–19]. Variability in production can be explained not only by factors that are beyond the control of farmers, such as input and output prices, but also by factors that are within the control of farmers, such as the quantity of inputs used (including seed, fertilizer, herbicides, and pesticides) [17,20,21]. Agricultural farming, including pineapple farming in Malaysia, is subject to and embodies a number of challenges that are similar in nature in terms of output variability [22]. According to the findings of a number of agricultural studies, the variability of output, also known as production risk, is measured by the variance of output, with the primary emphasis being placed on the specification that permits inputs to be either risk-increasing or risk-decreasing [16,23–27]. Because of how inputs are used, small farms in developing countries have a higher level of output risk or output variability [20,24,28].

The production trend for pineapple farming exhibits a significant degree of variation across a broad range. Farmers implement various forms of intensive production technology on their farms. Relying on production inputs can make the production process unpredictable (risky) and inefficient. In order to develop and expand this farming system in a way that is both environmentally friendly and feasible from a financial standpoint, an in-depth research is required. Emerging evidence suggests that small-scale farmers are traditionally more risk-averse [20,29,30]. They use an input bundle that differs from the economical optimal in that they use a greater proportion of risk-reducing inputs and a smaller proportion of risk-increasing inputs than a profit-maximizing producer would use. The state of exposure, which may include risk consequences of occurrences, is directly influenced by the risk attitude of the person making the decision. In addition, as a consequence of these impediments, farmers are unable to achieve the highest possible level of production in their operations.

Producing pineapple is inherently risky, which can lead to a significant range of yields. This is true of other agricultural endeavors as well [19,24,31,32]. Not only does the presence of risks have an effect on the yield, but it also has an effect on how producers utilize their inputs [33]. Farmers who are risk-averse will attempt to reduce production uncertainty via input selection [34]. However, depending on geography, the environment, and other factors, the input can either increase or decrease output variance (production risk) [27,35]. Therefore, an economic examination of the relationship between input use and output variability would be beneficial not only to farmers by increasing their understanding of the risk impacts of their input selections but also to policymakers involved in risk management in the pineapple business. In addition, if production risk imposes a major influence on a farmer's production decision, the farmer's technical efficiency performance may change substantially. This indicates that production risk and producer reaction must be integrated into empirical models used to estimate technical efficiency. In light of this, an economic investigation of the relationship between input use and output variability will not only benefit farmers by increasing their awareness of the risk consequences of their input choices, but it will also benefit policymakers who are involved in risk management in the pineapple industry. In addition, if the risk of production has a significant impact on the decisions that a farmer makes regarding production, the farmer's performance in terms of technical efficiency may be subject to significant shifts. This indicates that production risk needs to be incorporated into empirical models that are used to evaluate the technical efficiency of the farmers. This paper attempts to answer what the production risks with respect to the inputs used by pineapple smallholder farmers and what the factors affecting the technical efficiency of pineapple smallholder farmers are.

As a result, increasing the resource utilization efficiency in pineapple production is a significant challenge that must be overcome. The goal of this research focuses on generating sustainable growth in the production of pineapple cultivation. The presence of risk in the environment in which a crop is grown influences the decisions made by producers, the allocation of inputs, and, subsequently, the output supply. The risks that are connected to the inputs used in production are ubiquitous, and they have a significant impact on agricultural practices. It is essential to conduct an analysis of the ways in which risk influences the input decision made by the farmers, as well as the ways in which risk influences the farmer's efforts to achieve technical efficiency. It is crucial to quantify the output variability in Johor pineapple farmers given the growing popularity of research in agriculture that has incorporated production risk in the input usage of developing countries and demonstrated the importance of this component [24,36], In light of the government's efforts to improve pineapple production, it is essential to investigate how pineapple growers respond to the presence of production risks.

2. Literature Review

Numerous studies on agricultural farming employ efficiency analysis to address a variety of issues, such as comparisons of productivity and technical efficiency, the relationship between efficiency and profitability, and the optimal level of farm specialization [37–39]. Yet, there is a dearth of research in the literature that considers production risk in pineapple production empirically. It is feasible to integrate efficiency analysis with the risk function technique of Just and Pope. Concerning crop farming, a number of studies have addressed production risk using the Just-Pope approach [27,40,41] and efficiency using the SFA [27,42–47]. The presence of risk in production environments influences the farmers' decisions regarding input allocations and, consequently, output supply. The vast majority of empirical research has been focused on gaining an understanding of the reasons for low productivity, illuminating the consequences of technical inefficiency, and determining the causes of output variability resulting from input-related production risks. In addition, research has shown that the risks associated with agricultural outputs are affected by agricultural production inputs.

2.1. Production Inputs

Factors of production are found to be influencing yield variability and have been explored in several studies in the literature. A considerable amount of the literature has reported that labor has seen a risk-increasing input in agricultural production [32,48–52]. However, on the contrary, previous examples in the literature have also shown how labor has seen risk-decreasing inputs in production variability [19,24,33,34,53–57]. There have been several studies that have shown seeds to be risk-increasing inputs [24,32,33,49,53,58]. However, it was also pointed out in several reports in the literature that seeds are risk-decreasing inputs [50,59]. The importance of fertilizer in causing yield variability has been studied in various research, and the findings have been mixed and inconclusive. Several findings found that fertilizer was a risk-increasing input [33,48,53,56,57]. A similar approach has been pursued by others [24,32,50,51,60]; however, they found fertilizer as a risk-decreasing input. Meanwhile, a number of studies have also shown agrochemicals to be a risk-increasing input [24,59]. On the contrary, evidence from other studies suggests that agrochemicals are a risk-decreasing input in agricultural farming [32,50,61].

2.2. Socio-Economic Variables

Based on the selected efficiency studies above, the factors that determine the technical inefficiency of farmers, which are sourced from the socio-economic variables of the farmers, are reviewed. Older farmers are found to be more technically efficient than younger farmers [36]. On the contrary, in their studies, refs. [24,32] found that age was not significant in technical efficiency. The enrichment of the farmer's efficiency also depended on their level of education. Study [36] found that, in Ghana, the impact of education on efficiency levels was positive and significant. Similarly, the effect of education was affirmatively and significantly allied with agricultural productivity in developing countries [24,36,51,52,57]. However, several studies found negative and significant relationships between education and efficiency [62,63]. Several studies have reported that larger household sizes are less efficient [18,24,51]. Besides that, results on the impact of farming experience and on farmers' efficiency level showed that those with farming experiences are technically efficient [36,57]. Besides this, previous examples of the literature found that relying on an off-farming income is positively related to technical efficiency [18]; however, [19] showed that relying on an off-farming income is negative and significantly associated with technical efficiency in China. The contact between farmers and agricultural extension agents showed that those with a higher frequency are more efficient [20,24,32,51,59], while ref. [19] showed a negative and significant relationship. The impact of training and workshop participation is positively associated with technical efficiency, suggesting that participation in the seminars can boost the participant's productivity and livelihood by educating farmers on their proper resource utilization (i.e., inputs and technology). Similarly, the effect of training and workshop participation is affirmatively and significantly allied with agricultural productivity in developing countries [20,49] Among the different socioeconomic characteristics, the impact of farm size on technical efficiency is mixed and inconclusive. Various studies show a positive and significant relationship between farm size and technical efficiency [36,52], while others found a negative and significant relationship [19,51].

3. Methodology

In this study, we apply a stochastic frontier production function with an additive heteroskedastic error structure to estimate the production risk and technical efficiencies of pineapple farms, as well as the factors influencing them.

3.1. Integration of Risk into Stochastic Frontier Analysis

This research applied a stochastic frontier analysis that requires a parametric representation of the production technology. In addition, stochastic output variability is accounted for via a two-part error term. This technique was independently developed by Aigner et al. [64] and Meeusen and van den Broeck [65]. The model's general notation is as follows:

$$y_i = h(x_i; \alpha) \exp(\varepsilon_i) \quad (1)$$

where: y_i is the output of producer i (bounded above by the stochastic component $h(x_i; \alpha) \exp(\varepsilon_i)$, x_i is a vector of inputs used by producer i, α is a vector of unknown technology parameters, and $h(x_i; \alpha)$ is a production frontier. The composed error term is $\varepsilon_i = v_i - u_i$ where v_i captures the effect of pure noise in the data, which is attributed to the measurement error, extreme weather conditions, etc., and u_i is a one-sided error that captures the inefficiency effects. Nonetheless, the traditional specification of a stochastic production function has a characteristic that may severely limit its ability to accurately represent production technology. The implicit assumption that if any input has a positive effect on output, then this input must also have a positive effect on the output variability is a key shortcoming of the classical multiplicative stochastic specifications of production technology. Just and Pope [35] demonstrate that the effects of the input on the output should not be a priori correlated with the effects of inputs on the output variability. Therefore, the authors presented a more general stochastic specification model with two general functions: one that explained the effects of input on the mean output and another that specifies the impacts of inputs on the output variance:

$$y_i = h(x_i; \alpha) + g(z_i; \psi) v_i \quad (2)$$

where $h(x_i; \alpha)$ represents the mean production function and $g(z_i; \psi)$ is the stochastic component that indicates the relationship between the input level and output variability. The parameters α and ψ represent the mean and variance of the production function, respectively, whereas v_i is a stochastic term considered to be independent and identically distributed $N(0, 1)$. The output variability is explained by the variables z, which can be identical to the input variable x. Consequently, an input x_i can have varying effects on both the expected output level and output variance since the expected output is provided by $E(y) = h(x; \alpha)$ and the output variance is obtained by $V(y) = V(\varepsilon) = g^2(z; \psi)$. Appropriately, the effect of inputs has been divided into mean and variance effects. Therefore, the marginal influence of an input x, or the partial derivative of the variance with respect to this input, might be positive (risk-increasing input), negative (risk-reducing input), or zero (risk-neutral input). Battese et al. [66] additively incorporated the structure of the conventional SFA model independently proposed by Aigner et al. [64] and Meeusen and van den Broeck [65] into the Just and Pope [35] model. As a result, an SFA model with a flexible risk specification is derived by:

$$y_i = h(x_i; \alpha) + g(z_i; \psi) v_i \quad (3)$$

where y_i, x, $h(x_i; \alpha)$ $h(x_i; \alpha)$, $g(Z_i; \psi)$, and v_i, are as described above. The u_i is the error term that captures the technical inefficiency as $\delta u^2 = q(w)$. The introduction of u in the

Battese et al. (1997) [66] model differentiates it from the Just and Pope (1978) [35] model, which is the trademark of the SFA model. However, the issue with the equation of [66] is that it imposes the same variable inputs and a functional form on the heteroskedasticity in v and u. Study [27] extended the model of [66] by generalizing the model to allow the effects of the variable inputs and functional form to differ on the heteroskedasticity in v and u. The following is a generalized version of Kumbhakar's (2002) [27] SFA model with a flexible risk specification of:

$$y_i = h(x_{i;}; \alpha_i) + g(Z_i; \psi_i)v_i - q(w_i; \delta_i)u_i \tag{4}$$

where $q(w;\delta)$ is an additional function introduced to capture the effects of the farmer's socio-economic variables on the technical inefficiency effects, which also allows for heteroskedasticity in the inefficiency error term u, as $\delta u^2 = q(w)$. According to Equation (5) which is in the line proposed by [67], the technical efficiency of i-th farmer, represented by TE_i, is defined as the ratio of the mean production for the i-th farmer given the values of the inputs, x_i and its technical inefficiency effect, to the corresponding mean production if there were no technical inefficiencies of production. It is specified as:

$$TE_i = \frac{E(Y_i/x_i; u_i)}{E(Y_i/u_i = 0)} = \frac{h(x_i; \alpha_i) - g(x_i; \psi_i)u_i}{h(x_i; \alpha_i)} = 1 - \frac{ug(x_i; \psi_i)}{h(x_i; \alpha_i)} \tag{5}$$

Technical inefficiency (*TI*) is represented as:

$$TI_i = \frac{ug(x_i; \psi_i)}{h(x_i; \alpha_i)} \tag{6}$$

The technical efficiency, therefore, becomes:

$$TE_i = 1 - TI_i \tag{7}$$

To illustrate, in the absence of inefficiencies, Equation (6) shows that *TI* is positively related to the production risk function and negatively related to the mean output. This suggests that *TE* is also contingent and dependent on the production risk. Incorporating production risk into the stochastic frontier model is, therefore, essential. On the other hand, the conventional stochastic frontier model posits that *TE* is dependent on the one-sided random error only, $TE_i = \exp(-u_i)$. In the multiplicative form of the conventional stochastic frontier model, TE is expressed as follows:

$$TE_i = 1 - u\frac{h(x_i)}{h(x_i)} \tag{8}$$

Thus,

$$TI_i = u\frac{h(x_i)}{h(x_i)} = u_i \tag{9}$$

Nonetheless, as seen in Equation (8), technical inefficiency is not strictly proportional to the inputs. In the assessment of *TE* for this study, the production risk is accounted for as in Equation (5). The equation changes the *TE* scores based on the effects of inputs on the production risk, enabling the estimation of *TE* values that are unbiased.

3.2. Statement of Hypothesis

The hypotheses are formulated to determine the functional form that is appropriate for the data. In addition, they are formulated to determine if production risk in the inputs and technical inefficiency significantly explain the output variability. The hypotheses are developed to determine if exogenous and conventional input variables in the model of technical inefficiency explain the technical inefficiency. Hypothesis 1 to 3 were investigated using the generalized likelihood ratio statistic (LR), which stated the following. Firstly,

$H_0 : \alpha_{ij} = 0$. the parameters of the second order variable in the trans-log model are zero. This means that the Cobb-Douglas function is the best-fit model for the data. Secondly, $H_0 = \psi_1 = \psi_2 = \ldots = \psi_5 = 0$, the null hypothesis specifies that variability in the output is not explained by the production risk in the input factors. This implies that the coefficients of the variance function are zero. Thirdly, $H_0 : \lambda = 0$, the null hypothesis states that inefficiency effects are absent from the model. That is, the variance of the inefficiency term is zero, which implies that the ordinary least square (OLS) is more appropriate where $\log[L(H_0)]$ implies the log-likelihood of the null hypothesis and $\log[L(H_a)]$ denotes the log-likelihood of the alternative hypothesis. The values of $\log[L(H_0)]$ and $\log[L(H_a)]$ are provided by stochastic frontier analysis. When the value of likelihood ratio statistic (λ) is obtained, it is compared with the critical value $\chi^2 0.95$ according to the number of restrictions (the number of parameters specified to be zero). If λ is found to be greater than $\chi^2 0.95$, then the null hypothesis is rejected.

3.3. Data and Sampling Technique

The target population for the study is the pineapple smallholders in Johor. The list of all pineapple farming households that produced pineapple within 2019/2020 was obtained from the MPIB. Following the definition by MPIB [11], pineapple smallholders covered a total area of fewer than 40.47 hectares (100 acres) cultivated with pineapple or where pineapple cultivation is permitted and under valid ownership. This study employed farm-level cross-sectional data from randomly selected pineapple farmers in Johor. With the total of pineapple farmers in Johor reaching 899, this research needed a minimum sample size of 270 farmers. In arriving at the representative sample for the study from the list, multistage sampling and a simple random sampling procedure for the choice of districts and farmers were employed. In the first stage, seven districts in Johor were selected purposively according to their relative importance in terms of their acreage in pineapple production according to the data provided by MPIB. The seven districts are Muar, Batu Pahat, Pontian, Kluang, Johor Bahru, Kota Tinggi, and Segamat. In the second stage, farm households were randomly selected from each district, thus making a total sampling size of 290 (minimum n = 270) pineapple farm households. The smallholders of the research were selected at the district level.

4. Results and Discussion

4.1. Summary Statistics of Output and Inputs Variables

The variables used in the study are categorized into output variables, input variables, and factors affecting inefficiency, which are subdivided into demographic and institutional factors. The output (Y) in this study refers to the quantity of the harvested pineapple. The farmer's total output of the pineapple comprises the marketed and consumed output. Therefore, information on the quantities of pineapples harvested at the end of the cropping season was obtained. The total weight of the harvested crop was measured in kilograms per hectare (kg/ha). In pineapple production, the major production inputs include land, suckers, fertilizer, agrochemicals, labor, and hormones. These inputs are typical of any agricultural production operation. Other inputs, such as herbicides, weedicides, and insecticides, are also necessary because they are components of improved pineapple cultivation, and they are grouped as agrochemicals for this study. Consequently, the input variables for the analysis include land X_0, suckers X_1, fertilizer X_2, agrochemicals X_3, labour X_4, and hormones X_5. These variables are explained in the following.

Land (X_0) is the farm household's landholding devoted to pineapple cultivation. It is quantified by hectares and does not appear in the variable analysis as all other inputs are measured per hectare. Suckers (X_1) are the total quantity of suckers used in productions in the units of a number of suckers planted in the field per hectare. The fertilizer (X_2), input refers to the quantity of chemical fertilizers measured in kg per hectare when employed by the i-th farmer for the production period under study. Agrochemicals (X_3) are inputs that have been introduced for improved practices into the pineapple farming system. They are measured in litre per hectare (l/ha) and are composed of the quantity of herbicides, weedicides, and insecticides used by the *i*-th farmer during the research period. Labor (X_4) is described as the physical human effort. Labour was measured in man-day per hectare (man day/ha) for all farm operations carried out during the cropping season. The labor expended was measured using Norman [68] conversion ratio; one male adult working for one day is equal to one man day, one day of woman work, and one day of child work was estimated at 0.75 and 0.5 man-day, respectively. The total of one man-day is eight hours of man work.

Hormones (X_5) are composed of two types, namely artificial flower induction and fruit size manipulator. Although the quantity used is not as much as the fertilizer and chemicals, hormones play essential roles in ensuring optimum output. The applied hormones are measured in liters per hectare for the whole complete cycle usage in measuring the hormonal input use. The descriptive statistics of the inputs and output variables are presented in Table 1.

Table 1. Summary statistics of output and input variables for the mean and variance functions analysis.

Variable	Unit	Mean	Minimum	Maximum	Std. Dev.
Output					
Fresh pineapples	kg/ha	45,873.31	26,687.38	81,544.78	3831.87
Inputs					
Land	ha	0.92	0.40	4.45	1.42
Suckers	no/ha	36,406.91	20,000	45,695	1421.41
Fertilizer	kg/ha	1862.50	1111.50	2593.50	109.75
Labor	man-day/ha	137.71	86.45	185.25	11.67
Agrochemical	l/ha	27.37	12.35	61.75	4.07
Hormones	l/ha	12.89	6.67	17.29	0.85

4.2. Testing of Hypothesis

The results of various tests of the hypothesis conducted on the estimated coefficients are summarized in Table 2. A generalized likelihood ratio test was measured earlier to investigate the production risk and inefficiency analysis. In the first hypothesis, Cobb-Douglas is the best fit model for the data but was rejected in favor of the trans-log production function model at a five per cent level of significance. As a result, the trans-log production function model is the best fit for the data in this study, and it is used to perform a new generalized likelihood ratio test.

Table 2. Results of hypothesis tests for parameters in the stochastic frontier production function and inefficiency effects model.

Null Hypothesis	Log-Likelihood of H_0	Log-Likelihood of H_A	Test Statistic (λ)	Degree of Freedom	Critical Value (λ^2)	Decision
$H_0 : \alpha_{ij} = 0$	495.071	530.350	70.558	10	17.670	Reject H_0
$H_0 : \psi_1 = \psi_2 = \ldots = \psi_5 = 0$	495.071	530.350	70.558	4	8.761	Reject H_0
$H_0 : \lambda = 0$	495.071	530.350	70.558	1	2.706	Reject H_0

Note: Taken from Table 1 of [69] using 5% level of significance.

The second null hypothesis is that the variability in the output is not explained by the production risk in input factors, where $H_0 : \psi_1 = \psi_2 = \ldots = \psi_4 = 0$ is rejected at a 5% level of significance, indicating that the production risk of input factors is explained the variability in the output and should not be excluded from the model. The third null hypothesis is that the inefficiency effect is absent from the model, and ($H_0 : \lambda = 0$) is rejected at the 5% level of significance due to the fact that λ is 2.106 and the γ parameter associated with the variance of technical inefficiency effects in the stochastic frontiers, is estimated to be 0.816%. These results indicate that the effects of technical inefficiency contribute significantly to the total variability of the pineapple yield in the study area. The result also suggests that the stochastic frontier production function differs from the mean production function, which does not account for inefficiency effects. The rejection suggests that the conventional production function does not adequately represent the data.

4.3. Elasticity of Production and Returns to Scale

The estimates for the elasticity of the output with respect to the inputs of production are presented in Table 3. According to the parameters of the stochastic frontier model, all output elasticity for all of the inputs is positive. The positive sign indicates that the output will grow as the variables increase and vice versa. The relative output elasticity values for the suckers, fertilizer, agrochemicals, labor, and hormones are 0.916%, 0.106%, 2.046%, 0.445%, and 1.685%, respectively. This suggests that agrochemicals contribute the most to pineapple yield, followed by hormones, suckers, labor, and fertilizer.

Table 3. Output elasticity for inputs in the stochastic frontier production function.

Variable	Elasticity
Sucker	0.916
Fertilizer	0.106
Agrochemicals	2.046
Labor	0.445
Hormones	1.685
Returns to Scale (RTS)	5.199

A one percent increase in the number of agrochemicals used per acre will increase the yield by 2.046 percent, and vice versa. The result is congruent with research conducted by [70–73]. In addition, the findings of this study indicate that a one percent increase in the hormones per acre results in a 1.685 percent increase in the yield. Sucker used per acre outcomes in an output increase by 0.916 percent. This indicates that the optimal amount of sucker to be used has not yet been attained. Hence, increasing sucker usage in the research region will boost production. The conclusion is consistent with [48,74,75]. According to the findings, a one percent increase in the quantity of fertilizer used per acre will enhance the output by 0.106 percent. This indicates that greater fertilizer use favorably affects the output. In their study, ref. [76] observed comparable outcomes with fertilizer. A subsequent one percent increase in labor will result in a 0.445% rise in output. This emphasizes the significance of labor in the production of pineapples. The labor estimate is comparable to the findings of [57]. The analysis yielded a total output elasticity of 5.199 as the sum of the elasticity, also known as the return to scale (RTS), function coefficient, or total output elasticity. The joint proportional contribution of the factor inputs to the production is captured by the total output elasticity. When all inputs jointly increase by one percent, the pineapple output increases by around 5.199 percent, according to the economic interpretation of the captured RTS. The result of 5.199 is more than one, indicating that pineapple production in the research area has increasing returns to scale, according to estimations. In the research area, pineapple growers can still increase all factor inputs by five percent. As a result, the output will increase by 5.199 percent, which is higher than the proportionate increase in the input elements. This result was also similar to other studies in different countries, e.g., Nigeria [24] and Bangladesh [20]. This might reflect the fact that most of the farms are relatively small.

4.4. Production Risk Functions Estimates

The capacity to discern between an input effect on the mean output and its impact on the output variability is a key benefit of the Just and Pope (1978) [35] technique. In the production process, the input components explained the output variability. Some of the inputs are risk-reducing, while others are risk-increasing, providing crucial data for pineapple output stability. Table 4 shows the marginal output risk estimates for the inputs. The elasticities of the variance function can be discerned by looking directly at the parameter estimates from the variance function. The sign of elasticity indicates whether the input is risk increasing or risk decreasing. If the parameter is positive, the input has a risk-increasing effect, but if it is negative, the input has a risk-decreasing effect.

Table 4. Marginal production risk estimates for variance function.

Variables	Parameter	Coefficient	Std. Error	*p*-Value
Constant	ψ_0	−7.521 ***	13.729	0.000
Sucker	ψ_1	−4.144 ***	1.707	0.000
Fertilizer	ψ_2	6.819 ***	0.733	0.000
Agrochemicals	ψ_3	−0.180	0.269	0.503
Labor	ψ_4	−0.191	0.460	0.678
Hormone	ψ_5	1.552 **	0.776	0.046

Note: ** and *** denote significance at 5%, and 1% levels, respectively.

The estimated elasticity of the fertilizer and hormone is positive and significant, which implies that production risk increases with the increased use of these inputs. The risk-increasing effect of fertilizer was similar to previous studies conducted by [33,48,56,57]. The result of this study, exactly like those of other empirical studies mentioned earlier in Iran, Nigeria, the Philippines, and Russia, respectively indicates that greater use of fertilizer has a risk-increasing effect. The discovery that fertilizer increases risk is also consistent with the findings of [53] in Spain. The risk-increasing effect of hormones was found to be positive and significant at a five percent level of significance. A high density of hormonal applications to pineapple fruits will lead to decreasing productivity and increased production risk. Sucker or seed, on the other hand, has a significant risk-reducing effect on the production risk. This is consistent with findings from the previous literature in paddy production [50,53], maize production [59], and arable land farming in Germany [49]. On average, fertilizer and hormones are risk-increasing inputs, whereas suckers, agrochemicals, and labor are risk-reducing inputs. Fertilizers and hormones are anticipated to enhance the output value's variance significantly; therefore, they must be handled with care. Moreover, the use of suckers decreases the yield variability significantly. Another two variables, agrochemicals and labor, have a risk decreasing effect on the output variability. Although the effect of agrochemicals and labor are statistically insignificant, the result provides weak evidence that the existing usage of these two inputs is not sufficient to enable farmers to better mitigate against yield variability. Consistent with the findings of [50,61,73], this implies that the effective usage and management of agrochemicals can be employed to reduce output variability. Theoretically, an average risk-averse farmer in this study would be predicted to use less fertilizer and hormone due to the ability of these inputs to generate large output variations than a risk-neutral farmer in order to decrease output volatility. These results also indicate that risk-averse farmers can use more suckers in order to reduce the production risk and, hence, the revenue variability.

4.4.1. Inefficiency Production Model Estimates

Understanding the sources of technical efficiency and its extent is very important for policy-making to address the problem of farm households. In this regard, the socio-economic and institutional conditions specific to farmers were hypothesized to affect the level of inefficiency for pineapple smallholders in the study area. Four of the eight variables utilized in this model exhibit the expected signs and three of them were statistically significant. A negative coefficient shows that the variable increases pineapple production's efficiency (decreases inefficiency) and vice versa. The findings of technical inefficiency provided in Table 5 indicate that technical inefficiency is significantly reduced by farming experience, extension visits, and seminar/workshop participation.

Table 5. Maximum likelihood estimates for parameters of inefficiency effect of trans-log stochastic production model.

Variables	Parameter	Coefficient	Std. Error	*p*-Value
Constant	δ_0	3.593	7.952	0.651
Age	δ_1	0.043	0.075	0.563
Education	δ_2	0.003	0.206	0.985
Household Size	δ_3	0.110	0.325	0.735
Farming Experience	δ_4	−0.736 **	0.339	0.030
Off farm activities	δ_5	0.774	1.206	0.521
Extension Visit	δ_6	−2.131 ***	0.810	0.009
Membership	δ_7	−1.205	1.671	0.471
Seminar	δ_8	−3.856 ***	1.358	0.005

Note: ** and *** denote significance at 5%, and 1% levels, respectively.

4.4.2. Farming Experience

The longer a person stays at a job, the greater the likelihood that they will become an expert. Farming contains numerous dangers and uncertainties; therefore, a farmer must have extensive experience on the farm to be competent enough to deal with all of its unforeseen changes. Regardless of their level of education, a farmer who has been cultivating pineapple for many years is likely to be more educated about the rainfall pattern, the prevalence of pests and diseases, and other agronomic characteristics in the region than a farmer who is new to the business. The expected sign is negative, and the analysis indicates that experience has a negative effect on technical inefficiency, suggesting that the more experienced a farmer is, the less inefficient he or she will be. This result is similar to the findings of maize [77–79], paddy ([80–83], and vegetable farming [84]. This implies that as years of experience increase the knowledge and skills in utilizing farm resources, it increases the level of production from a given set of inputs.

4.4.3. Extension Visits

Another factor worth considering as a variable affecting TE is extension visits by the extension officers or agricultural officers to the smallholders' farms. Refs. [85,86] asserted that higher extension visits to the farmers enable them to implement recommended cultural practices into production in order to increase efficiency. Farmers are expected to receive consulting services and training from extension agents in order to increase their efficiency. This variable has a negative effect on inefficiency and is statistically significant at 1%. This indicates that the more knowledge the farmer gains from extension programs, the less inefficient he is. The outcome seen is consistent with the previous literature on agricultural production [79,82,87–94]. It has long been assumed that farmers who make more use of extension services, both in terms of seeking guidance and participating in training programs, are more technically efficient than their counterparts who make fewer or no such efforts.

4.4.4. Seminar Cum Training

Farmer participation in seminars and training had a negative and significant relationship with technical inefficiency in pineapple production. The farmers' seminar attendance was measured by assessing whether or not they received training on the pineapple cultivation cycle. This indicates that the farmer became less inefficient as he or she learned via training and lecturing. Better farming techniques could be encouraged by giving farmers access to updated information, training, and demonstrations. As a result, the research factored in the availability of training as a means to improve productivity and found a statistically significant correlation between training accessibility and technical productivity in agricultural families. This was in line with the findings obtained by [88,93,95,96]. The inefficiency of a farm is reduced when the manager has received better training. Thus, farmers, especially experienced farmers, should attend seminars and training frequently, where this training could retrain farmers on improved production practices to maximize productivity since farmers may still be clinging to their standard old techniques of production.

4.5. Technical Efficiency Score

For the entire study region, the stochastic frontier specification model predicted the average technical efficiency of pineapple farms at the farm level. The estimations are shown in Table 6. The average technical efficiency is approximately 0.681%, indicating that the average farm produced only 68.1% of the maximum possible output for the given input levels during the analyzed production period. It also implies that there is still a 31.9% opportunity to increase the output of decision-making units (DMUs) by adopting the technology of best-practice DMUs. The maximum estimated technical efficiency is 0.990, while the minimum is 0.401. Around 12.7 percent of the farmers had a mean technical efficiency greater than 0.91, 12.4 percent had a mean technical efficiency greater than between 0.8 and 0.9, and 14.9 percent had a mean technical efficiency greater than 0.7 or equal to 0.7. A total of 17 percent. had a mean technical efficiency greater than 0.6 or equal to 0.7, 12 percent had a mean technical efficiency of 0.5 or equal to 0.6, and 18.8 percent had a mean technical efficiency greater than 0.4 or equal to 0 and were individuals who were adversely affected by a variety of causes, including production risk, socio-economic, and institutional constraints.

Table 6. Technical efficiency distribution of farmers in Johor, trans-log model.

Efficiency Scores	Frequency	Percent (%)
1.00	0	0.00
(0.91, 1)	42	12.76
(0.81, 0.90)	41	12.46
(0.71, 0.80)	49	14.89
(0.61, 0.70)	56	17.02
(0.51, 0.60)	40	12.15
(0.41, 0.50)	62	18.84
(0.31, 0.40)	0	0.00
(0.21, 0.30)	0	0.00
(0.10, 0.20)	0	0.00
Total	290	100
Mean	0.681	
Minimum	0.401	
Maximum	0.990	
Std. Dev.	0.175	

Pineapple producers in Johor have a technical efficiency score that ranges from 0.401 to 0.990, with an average of 0.681. There was room for growth in pineapple cultivation in the face of such low production efficiencies, even with the farmers' existing levels of technology. Based on the results of the SFA model, the average farm household's TE is 31.9% lower than it could be if they were more effective at producing these crops with the same number of inputs. As an alternative, if farmers were more efficient, they could maintain the present outputs of these crops while using fewer inputs. Both input orientation (input minimization) and output orientation (output maximization) have the same CRS-assumed efficiency ratings (output maximization). Therefore, if the inputs were held constant and efficiency was measured by increasing outputs, the efficiency score would also suggest raising outputs by 31.9%. Therefore, this finding demonstrates that smallholder farmers in the research area suffer from severe technological inefficiency in pineapple production. Efficiency levels, on average, were in line with those found in earlier research conducted in underdeveloped nations.

5. Conclusions

5.1. Policy Implications

As anticipated, all inputs (sucker, fertilizer, labor, agrochemicals, and hormones) were associated with an increase in the average pineapple production. In addition, the results indicated that sucker had a negative and significant effect on the output variability and was, thus, regarded as risk-reducing input. Both fertilizer and hormones have significant effects on the yield variability of pineapple; therefore, they are inputs that increase the output risk. Therefore, policy strategies should not be limited to merely disseminating information to farmers that emphasize the appropriate use of technological inputs, particularly fertilizers and hormones, but by providing farmers with essential information regarding the optimal rate, time, and method of application. However, they should also be complemented with agronomic management practices to reduce the risk of attack from inappropriate input applications, pests, and diseases. Moreover, efforts to enhance sucker-based assistance should be prioritized. The fact that some factors have shown to have a significant contribution to the pineapple smallholders' technical efficiency (extension visit and seminar) implies that pineapple production could be improved upon if efforts were stepped up to appropriately improve the usage of these factors as there is potential for increasing farm efficiency by adopting current farming technologies. More extension of knowledge given to farmers on these factors is, therefore, recommended. Thus, such knowledge could help improve the efficiency with which these factors are being utilized. Farmers should be frequently educated on the current, diverse culturing skills and techniques for pineapple production. Thus, the knowledge could be disseminated to Malaysian pineapple farmers through reskilling and upskilling programs such as short courses, mentoring, and the application of smart farming practices.

Some factors have shown significant contribution to pineapple technical efficiency; this implies that pineapple production could be improved upon if efforts were stepped up to increase the farms' efficiency appropriately, then there would be a potential improvement in productivity. In achieving the determined objective, more extension officers should be recruited to guide the farmers on the use of improved variable inputs. It is well-established that agricultural extension officers play a crucial role in the agricultural sector of any country and that their importance grows exponentially because they are the second most important part of the agricultural sector, after farmers. This is because the extension officer's job ensures that the farming community is always aware of the most recent and cutting-edge information regarding farming techniques and how to maximize the efficiency of their agricultural output. An extension officer's presence in a rural area can have a significant impact on agricultural output if they are well-informed on the latest developments in their field. Thus, the knowledge could improve the efficiency with which the factors are being utilized. Farmers should be educated on the current agricultural techniques, diverse culturing skills, and techniques for pineapple production. Thus, the knowledge could be disseminated to pineapple farmers in the study area through workshops, seminars, and other teaching methods.

Revealing the significant role of participation in seminars in terms of decreasing the inefficiency of pineapple farmers, relevant government agencies, including MPIB in particular, should make attendance compulsory, attending any seminar or workshop organized by the government authority to improve the knowledge of the farmers. This is because the knowledge they receive can assist them in improving their managerial ability in farm operation and management, thus increasing efficiency performance, productivity, and pineapple output. The authority should also ensure that at every point in time, the extension agents are shoulder to shoulder with the current best farm practices. Moreover, government agencies should prioritize the onsite visit to monitor and engage with the actual progress of the pineapple farmers. This will impact the quality of information conveyed to farmers and should result in fewer production system inefficiencies.

5.2. Summary

Estimating the level of technical efficiency and the production risk faced by pineapple producers in Johor was the primary focus of this research. The model of Just and Pope (1978) [35] was modified by Kumbhakar (2002) [27] to include technical inefficiencies within the framework of survey data and was used to estimate a production function allowing the incorporation of the production risk. The conclusion of the study is that the trans-log production function model best fits the data. Applying the model to 290 pineapple farms in Johor, the study examined the mutual influence of input utilization and output variation while estimating technical efficiency. According to the results of the analysis, technical inefficiency increases the variability of pineapple output in Johor. Nevertheless, the model suggests that production risk significantly contributes to the volatility of pineapple production.

Variability in the pineapple output is mostly attributable to technical inefficiencies and production risk, and this was congruent with findings by [27,45,46]. This suggests that while examining the evolution of pineapple production in Johor, greater emphasis should be placed on the presence of the production risk and related farmer behavior. Regarding research on the technical efficiency of pineapple farms, in particular, disregarding the effect of risk on agricultural output may result in inaccurate estimates of technical efficiency. Due to the uncertainty associated with agricultural production processes, such as crops and pineapples in general, and especially when uncertainty is persistent, the present study demonstrates that the theoretical framework for investigating technical efficiency must be expanded to incorporate the production risk. However, under the premise of risk neutrality with regard to production risk in inputs, estimations of the technical efficiency of pineapple farms in Malaysia are fundamentally biased. Obviously, such skewed and biased estimations could lead to misleading policy recommendations based on the findings of this study.

Production risk is simultaneously explained by sucker, fertilizer, labor, agrochemicals, and hormones. The output deviations caused by technical inefficiency are more pronounced than the output deviations caused by the production's pure noise component (lambda value of 2.010). The combined effects of farm inefficiency factors are able to explain the variance in technical efficiency, despite the insignificance of some individual variables. The conventional input components, i.e., sucker, fertilizer, labor, agrochemicals, and hormones, are crucial to the growth of pineapple output. In the production process, all conventional input components (sucker, fertilizer, labor, agrochemicals, and hormones) increase the mean output. The production technology characterizing pineapple farms in the study area displays increasing returns to scale (5.199). Fertilizers and hormones are estimated to be risk-increasing inputs, while fertilizer, agrochemicals, and hormones are estimated to be risk-reducing inputs. Therefore, these inputs can be used to mitigate the production risk.

The average technical efficiency of the farms assessed under SFA is 68.1%. The current mean technical efficiency estimates present the chance to increase pineapple output by 31.9 percent under the SFA approach without employing extra resources. Producers that are more experienced have more extension contacts, have a higher number of seminar participants, are less inefficient, and were found to be the factors that would improve technical efficiency in the study area. The role of MPIB in providing extension visits and organizing seminars to improve efficiency is also evident in this work. This justifies by strengthening the extension agents, and more knowledge dissemination not only reduces inefficiency but also increases profits among the pineapple smallholders in Johor. In a nutshell, this research investigated the relationship between input use and output variability and has shown how it will not only benefit farmers by increasing their awareness of the risk consequences of their input choices but will also benefit policymakers who are involved in risk management in the pineapple industry.

Author Contributions: Conceptualization, M.N.S., N.H.K., N.M.N., J.L. and M.Z.M.; Data curation, M.Z.M.; Formal analysis, M.Z.M.; Investigation, M.Z.M.; Methodology, M.N.S. and M.Z.M.; Project administration, M.N.S., N.H.K., N.M.N. and J.L.; Resources, J.L.; Supervision, M.N.S., N.H.K., N.M.N. and J.L.; Validation, M.N.S., N.H.K., N.M.N. and J.L.; Writing—original draft, M.Z.M.; Writing—review and editing, M.Z.M. All authors have read and agreed to the published version of the manuscript.

Funding: The research was funded by Pembiayaan Yuran Prosiding Berindeks (PYPB), Universiti Teknologi MARA (UiTM), Malaysia.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all participants involved in the study.

Data Availability Statement: The data used in this study are available upon request from the corresponding author.

Acknowledgments: We express sincere gratitude to the Universiti Teknologi MARA, Universiti Putra Malaysia and the Ministry of Education Malaysia.

Conflicts of Interest: The authors declare no conflict of interest.

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